

## PATENT ABSTRACTS OF JAPAN

(11)Publication number : 10-171988

(43)Date of publication of application : 26.06.1998

(51)Int.Cl.

G06T 7/00

(21)Application number : 08-339114

(71)Applicant : MATSUSHITA ELECTRIC IND CO LTD

(22)Date of filing : 05.12.1996

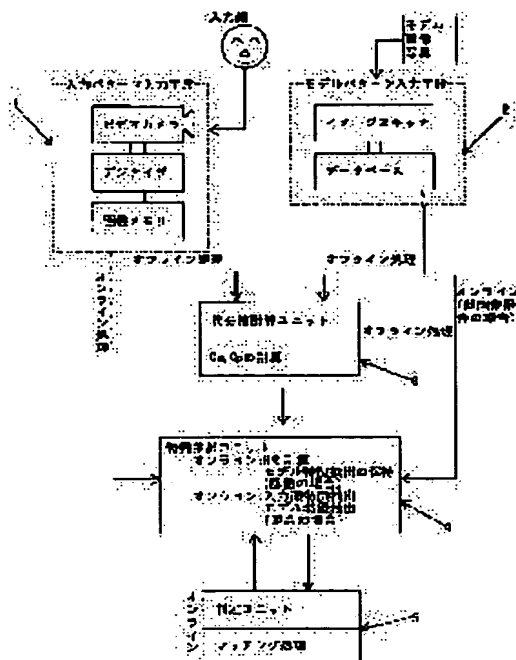
(72)Inventor : NAGAO KENJI  
SOMA MASAYOSHI

## (54) PATTERN RECOGNIZING/COLLATING DEVICE

## (57)Abstract:

**PROBLEM TO BE SOLVED:** To accurately perform a collation to a person even about any face photograph by previously obtaining a conversion to make a model and a fluctuation amount be orthogonal to each other from many face pictures and face photographs, extracting a characteristic using this conversion and collating a face not attaching to any group of models to a photograph.

**SOLUTION:** A covariance calculating unit 3 fetches picture data from an input pattern input means 1 and a model pattern input means 1, and calculates a covariance matrix as regarding one picture data as a vector. A characteristic extracting unit 4 calculates a conversion matrix from the covariance matrix, and at the same time, performs a vector conversion as regarding one picture data as a vector and calculates a characteristic vector. Then, the selection of a characteristic space in that the space of the model pattern and the space of model-input varied vector are orthogonal is performed, and the collating processing of the face picture and the face photograph by the input pattern input means 1, the model pattern input means 2, the covariance calculating unit 3 and the determination unit 5.



## LEGAL STATUS

[Date of request for examination] 17.07.2002

[Date of sending the examiner's decision of rejection]

[Kind of final disposal of application other than the examiner's decision of rejection or application converted registration]

[Date of final disposal for application]

[Patent number] 3729581

[Date of registration] 14.10.2005

[Number of appeal against examiner's decision of rejection]

[Date of requesting appeal against examiner's decision of rejection]

[Date of extinction of right]

Copyright (C); 1998,2003 Japan Patent Office

## \* NOTICES \*

JPO and NCIP1 are not responsible for any damages caused by the use of this translation.

- 1.This document has been translated by computer. So the translation may not reflect the original precisely.
- 2.\*\*\*\* shows the word which can not be translated.
- 3.In the drawings, any words are not translated.

## CLAIMS

## [Claim(s)]

[Claim 1] A model pattern input means to input the model pattern M (for it to also be called model \*\* KUTORU), An input configuration input means to input input configuration I for recognition (for it to also be called an input vector), A model vector covariance input means to input the covariance matrix Cm of a model vector, A model-input fluctuation covariance input means to make learn beforehand the covariance matrix Cp of the fluctuation to the input configuration which corresponds from each model pattern, and to input it, Weighted average with the model-input fluctuation covariance matrix inputted from the model vector covariance matrix inputted from said model vector covariance input means, and said model-input fluctuation covariance input means  $Cs^{**}\alpha Cm + (1-\alpha) Cp$  ( $\alpha$  is the real number of  $0 < \alpha < 1$ ) ... (1)

Matrix Cs of the output of a covariance weighted average generation means to be alike, to follow and take and to newly generate Matrix Cs, and said covariance weighted average generation means  $Cs = (AQ^{-1/2} (Q^{-1/2}AT)^{-1})$  ... (2)

(A is the normalization characteristic vector matrix of Cs)

(Diagonal matrix which consists of characteristic value to which Q corresponds)

(— Q — the square root matrix of  $1/2Q$ , and AT — transposed-matrix) of A — like — spectral decomposition — carrying out — this — matrix  $D^{**}Q^{-1} / 2AT$  ( $Q^{-1/2}$  are the inverse matrix of the square root matrix of Matrix Q)

The diagonalization means of \*\*\*\*\* 1st, and matrix DCmDT which changed the model pattern covariance matrix Cm according to Matrix D  $DCmDT = BPBT$  ... (3)

(B is the normalization characteristic vector matrix of DCmDT)

output  $Q^{-1/2}$  of the 2nd diagonalization means which carries out spectral decomposition like (the diagonal matrix which consists of characteristic value to which P corresponds), and acquires Matrix B, and said 1st and 2nd diagonalization means — AT and B — using —  $H^{**}WBTQ^{-1/2}AT$  ... (4)

( $W^{**}diag(\alpha_1, \alpha_2, \dots, \alpha_n)$  and (non-negative-number) with  $\alpha_i$  [ suitable ]) are followed, Matrix H is generated and held, and it is from the model pattern M and input configuration I to the run time of recognition.

$M^{**}HM, I^{**}HI$  ... (5)

alike — following — each — a feature vector —  $M - I$  — extracting — a feature extraction — a means — said — a feature extraction — a means — having extracted — an input configuration — I — a feature vector — I — a model — a pattern — M — a feature vector — M — distance —  $\|M - I\|$  ( $\|*\|$  is Euclidean distance) ... (6)

The pattern recognition and the collating unit characterized by providing a judgment means to judge to which model an input configuration corresponds by this by finding out the model pattern with which \*\*\*\* also has a small feature vector (recognition).

[Claim 2] Similarity of the feature vector of a model pattern and an input configuration  $(M - I) / (\|M\| \|I\|)$  ... (7)

For the inner product of a vector, and  $|*|$ , ((\* and \*) are the pattern recognition and a collating unit according to claim 1 characterized by providing a judgment means to evaluate according to magnitude-of-a-vector) and to judge whether this value of that input configuration and model is the same by whether it is more than constant value.

[Translation done.]

## \* NOTICES \*

JPO and NCIP are not responsible for any damages caused by the use of this translation.

- 1.This document has been translated by computer. So the translation may not reflect the original precisely.
- 2.\*\*\*\* shows the word which can not be translated.
- 3.In the drawings, any words are not translated.

## DETAILED DESCRIPTION

## [Detailed Description of the Invention]

[0001]

[Field of the Invention] This invention relates to the pattern recognition and the collating unit which recognizes and judges a fluctuation component especially in the space changed so that it might intersect perpendicularly with a model component in the pattern recognition and the collating unit for authentication of ID system using a person face, and a license pocket person, a man machine interface, or security about the pattern recognition and the collating unit used for the information compression of the user identification which used the photograph of his face etc., or a low bit rate communication link.

[0002]

[Description of the Prior Art] Based on the secondary statistic (covariance) calculated from the model set registered into the database, in distribution of a pattern, i.e., the data space mentioned above, the method which attracts attention recently in the technical field of pattern recognition (for example, face image recognition and speech recognition) presumes the part which the set of a pattern occupies, and performs the feature extraction from a pattern based on this. For example, KL (Karhunen-Loeve) expansion method learned well performs a feature extraction by KL expansion, and is reference. M.Turk & [ A.Pentland] "Face Recognition Using Eigenfaces" Proceedings of IEEE, CVPR91. It is stated in detail and there are many to which other approaches applied to this correspondingly.

[0003] With the KL method, they are the model image  $M$  and input configuration  $I$ .  $M = \sum \gamma_i E_i$   
 $I = \sum \gamma_i' E_i \dots (8)$

(For  $\gamma_i$ ,  $i$  component of  $M$  and  $\gamma_i'$  are  $i$  component of  $I$ )

It approximates by the linear combination of  $p$  base vectors  $E_i$  ( $i = 1 \dots p$ ), and collating is taken between approximation data as shown for (taking the sum about  $i = 1 \dots p$ ).

[0004] The characteristic vector corresponding to  $p$  things (for example, about 100 pieces) is used for the KL method from what has the large characteristic value of the covariance matrix obtained from  $w$  instruction pattern data as this base vector. If the base vector constitutes space, it dissociates best, namely, it will be easy to distinguish and the instruction data by which (1) projection was carried out will become.

(2) The noise contained in a pattern can take and remove the component (fluctuation) which appears irregularly. It is thought that it has the advantage to say. The point which it should be careful of in this KL method is a point which assumes that distribution of the pattern vector presumed based on the statistic obtained from a model pattern set has generality, i.e., it is about applied also in the pattern of an input.

[0005] For example, in face image recognition, when the fluctuation from the model of an input configuration is not so large, also experimentally, it is actually checked that a recognition rate with a very high precision is attained.

[0006]

[Problem(s) to be Solved by the Invention] However, in the above conventional methods, when the difference between an input configuration and a model became large, there was a problem that sufficient recognition rate could not be offered. This is a serious problem which generates when environments, such as lighting conditions at the time of photography, change a lot by the input image and the model image in image recognition, and is often generated actually.

[0007] The cause of the above-mentioned problem in a conventional method originates in assuming that it can presume general distribution of a pattern only using the statistic of the model pattern contained in a database.

[0008]

[Means for Solving the Problem] In order to solve this problem, in this invention, in addition to the statistic obtained from a model set, the statistic which caught change from the model of an input configuration is also made to learn beforehand, and is used. Therefore, a model vector covariance input means to input the covariance matrix  $C_m$  (presumption of the statistical property of a pattern) of a model pattern in this invention, A model-input fluctuation covariance input means to make learn beforehand the covariance matrix  $C_p$  (statistical information which shows the property of change) of the fluctuation to the input configuration which corresponds from each model pattern, and to input it. Weighted average with a model vector covariance matrix and a model-input fluctuation covariance matrix  $C_s = \alpha C_m + (1 - \alpha) C_p$  ( $\alpha$  is the real number of  $0 < \alpha < 1$ ) ... (1)

A covariance weighted average generation means to be alike, to follow and take and to newly generate Matrix  $C_s$ , and  $C_s = (A Q^2 / 2) (Q^2 / 2 A^T) \dots (2)$

( $Q$  the square root matrix of  $1/2 Q$  and  $A^T$  transposed matrix of  $A$ )

(A is the normalization characteristic vector matrix of Cs)

It is the matrix DCmDT which changed the first diagonalization means and model vector covariance matrix Cm which carries out spectral decomposition like (the diagonal matrix which consists of characteristic value to which Q corresponds), and obtains matrix  $Q^{-1/2}AT$  using matrix  $D^{**}Q^{-1/2}AT$ .  $DCmDT=BPBT$  ... (3)

(B is the normalization characteristic vector matrix of DCmDT)

the 2nd diagonalization means which carries out spectral decomposition like (the diagonal matrix which consists of characteristic value to which P corresponds), and acquires Matrix B, and these matrix  $Q^{-1/2}AT$  and B — using —  $H^{**}WBQTQ^{-1/2}AT$  ... (4)

( $W^{**}diag(\alpha_1, \alpha_2, \dots, \alpha_n)$  and (non-negative-number) with  $\alpha_i$  [ suitable ]) are followed, Matrix H is generated and held, and it is from the model pattern M and input configuration I to run time.  $M^{**}HM, I^{**}HI$  ... (5)

It has a feature-extraction means for it to be alike, and to follow and to extract a feature vector.

[0009] In the pattern recognition and the collating unit of claim 1, the feature vector of an input face is received further.  $\|M' - I'\|$  ( $\|*\|$  is Euclidean distance) ... (6)

It has a judgment means to elect the model in which a \*\*\*\*\* value has the smallest feature vector as a recognition result.

[0010] Moreover, the pattern recognition and the collating unit of claim 2 are the similarity of the feature vector of a model and an input configuration further.  $(M' - I') / (\|M'\| \|I'\|)$  ... (7)

( $(* \text{ and } *)$  evaluate the inner product of a vector, and  $\|*\|$  according to magnitude-of-a-vector), and this value has a judgment means by which an input configuration judges whether it is a thing corresponding to that model by whether it is more than constant value.

[0011] Change of the input configuration from a model pattern can control to intersect perpendicularly with the space which a model set occupies by diagonalizing the covariance Cs weighted-average-sized above and the model vector covariance Cm using the diagonalization means 1 and 2, and performing a feature extraction according to the acquired matrix H. It is surely matched in the model corresponding to an input by the description of a direction which intersects perpendicularly with the space which a model occupies in the last process of recognition and collating by this even when the difference between a model and an input configuration is great being disregarded. Hereafter, this detailed mechanism is explained.

[0012]

[Embodiment of the Invention] A model pattern input means by which invention indicated to claim 1 of this invention inputs the model pattern M (it is also called model \*\* KUTORU), An input configuration input means to input input configuration I for recognition (for it to also be called an input vector), A model vector covariance input means to input the covariance matrix Cm of a model vector, A model-input fluctuation covariance input means to make learn beforehand the covariance matrix Cp of the fluctuation to the input configuration which corresponds from each model pattern, and to input it, Weighted average with the model-input fluctuation covariance matrix inputted from the model vector covariance matrix inputted from said model vector covariance input means, and said model-input fluctuation covariance input means  $Cs^{**}\alpha Cm + (1-\alpha) Cp$  ( $\alpha$  is the real number of  $0 < \alpha < 1$ ) ... (1)

Matrix Cs of the output of a covariance weighted average generation means to be alike, to follow and take and to newly generate Matrix Cs, and said covariance weighted average generation means  $Cs = (AQ^{1/2}(Q^{1/2}AT))$  ... (2)

(A is the normalization characteristic vector matrix of Cs)

(Diagonal matrix which consists of characteristic value to which Q corresponds)

( $Q$  — the square root matrix of  $1/2Q$ , and  $AT$  — transposed-matrix) of A — like — spectral decomposition — carrying out — this — matrix  $D^{**}Q^{-1/2}AT$  ( $Q^{-1/2}$  are the inverse matrix of the square root matrix of Matrix Q)

The diagonalization means of \*\*\*\*\* 1st, and matrix DCmDT which changed the model pattern covariance matrix Cm according to Matrix D  $DCmDT=BPBT$  ... (3)

(B is the normalization characteristic vector matrix of DCmDT)

output  $Q^{-1/2}$  of the 2nd diagonalization means which carries out spectral decomposition like (the diagonal matrix which consists of characteristic value to which P corresponds), and acquires Matrix B, and said 1st and 2nd diagonalization means —  $AT$  and B — using —  $H^{**}WBQTQ^{-1/2}AT$  ... (4)

( $W^{**}diag(\alpha_1, \alpha_2, \dots, \alpha_n)$  and (non-negative-number) with  $\alpha_i$  [ suitable ]) are followed, Matrix H is generated and held, and it is from the model pattern M and input configuration I to the run time of recognition.

$M^{**}HM, I^{**}HI$  ... (5)

alike — following — each — a feature vector —  $M - I$  — — extracting — a feature extraction — a means — — said — a feature extraction — a means — having extracted — an input configuration —  $I$  — a feature vector —  $I - M$  — — a model — a pattern — M — a feature vector —  $M - I$  — — distance —  $\|M - I\|$  ( $\|*\|$  is Euclidean distance) ... (6)

\*\*\*\* also has an operation that it can recognize except for a changed part of an input configuration as compared with a model pattern, by finding out the model pattern which has a small feature vector, providing a judgment means to judge to which model an input configuration corresponds by this (recognition), and making model space and fluctuation space intersect perpendicularly.

[0013] Invention of this invention according to claim 2 is the similarity of the feature vector of a model pattern and an input configuration.  $(M' - I') / (\|M'\| \|I'\|)$  ... (7)

( $(* \text{ and } *)$  have an operation that it can collate with a model pattern except for a changed part of an input configuration, when the inner product of a vector and  $\|*\|$  are evaluated according to magnitude-of-a-vector), and this value possesses a judgment means to judge whether that input configuration and model are the same by

whether it is more than constant value and makes model space and fluctuation space intersect perpendicularly.

[0014] (Gestalt of the 1st operation) The gestalt of operation of the 1st of this invention is face image recognition equipment which elects the face image which is in agreement with the input face image inputted from the video camera etc. from the database of a model image photograph. Hereafter, the pattern recognition and the collating unit of this invention are explained using Fig. 1 about the case where it applies to face image recognition.

[0015] The input configuration input means 1 is constituted by the video camera which photos an input face, the digitizer which changes the analog video signal of a video camera into a digital signal, and the image memory which memorizes a digital video signal. The model pattern input means 2 is constituted by the image scanner which scans and inputs a model image photograph, and the database which stores the model image photograph inputted from the image scanner as a digital image file. The covariance count unit 3 is count equipment which calculates a covariance matrix by inputting image data from the input configuration input means 1 and the model pattern input means 2, and considering that one image data is a vector. The feature-extraction unit 4 is count equipment which calculates a feature vector by considering that one image data is a vector and carrying out vector conversion by the transformation matrix while calculating a transformation matrix from a covariance matrix. The judgment unit 5 is count equipment which calculates the distance and the include angle between feature vectors. These count equipments may be constituted using a general-purpose processor, and may be constituted using the processor of dedication, such as DSP.

[0016] By the input configuration input means 1, the model pattern input means 2, the covariance count unit 3, and the feature-extraction unit 4, a feature space which makes the space of a model pattern and the space of a model-input fluctuation vector orthogonalize is selected as an off-line process, and the input configuration input means 1, the model pattern input means 2, the covariance count unit 3, and the judgment unit 5 perform recognition processing on-line.

[0017] First, off-line processing is explained. Generally the dimension (for example, dimension of the part which a face image occupies in the whole image space) of the space which a pattern occupies in data space is quite small (for example, 100 dimensions) compared with the dimension (it is 100,000 dimensions if for example, the number of pixels is 100,000) of the space of a basis in many cases. Similarly, the fluctuation vector of a model-input also occupies the space of a low dimension in data space. First, the covariance matrix  $C_m$  which shows the statistical inclination of a model pattern is inputted from a model vector covariance input means. The model pattern inputted from the model pattern input means is used for this covariance matrix  $C_m$ .  $C_m = \sum M M^T \dots (9)$

( $M^T$  takes the transposed matrix of Matrix  $M$ , and the sum about all sample models  $\{M\}$ .) — it follows, and although direct count can be carried out, it is satisfactory even if obtained by other approaches. What is necessary is just to show distribution (covariance) of a model pattern. With this operation gestalt, the model pattern covariance  $C_m$  is calculated using the model person face image set  $\{M\}$  inputted into the database of the image scanner equipment which is the model pattern input means 2. Here, since it is easy, the mean vector of a model vector is set to 0. When that is not right,  $M$  (a set  $\{M\}$  averages  $M_a$  ( $M - M_a$ )) is used.

[0018] Moreover, the covariance matrix  $C_p$  which shows the statistical property of the difference ( $M - I$ ) of an input configuration and a corresponding model is inputted from a model-input fluctuation covariance input means, and the fluctuation inclination of an input is made to learn. This covariance  $C_p$  uses the sample group of the input configuration inputted from an input configuration input means, and the difference of a corresponding model.  $C_p = \sum (M - I)(M - I)^T \dots (10)$

( $M - I$ ) ( $I$  is the transposed matrix of a matrix ( $M - I$ ))

(sum was obtained — all ( $M, I$ ) — it takes about a pair.) — it follows, and although direct count can be carried out, it may be obtained by other approaches. What is necessary is just to show distribution (covariance) of a difference vector. With this operation gestalt, the model-input fluctuation vector covariance  $C_p$  actually inputs an input face vector  $\{I\}$  (input configuration), and is calculated according to a formula 10 from a difference with a corresponding model face pattern.

[0019] Count of the above two covariances  $C_m$  and  $C_p$  is carried out by the common covariance count unit 3. The information on these covariances is sent to the feature-extraction unit 4.

[0020] In the feature-extraction unit 4, first, the weighted average  $C_s$  of two covariances is calculated according to a formula 1, and the feature-extraction matrix  $H$  is generated and held through coincidence diagonalization of  $C_s$  and  $C_m$ . In the case of image recognition equipment, a feature vector  $\{M'\}$  is extracted from a model image vector  $\{M\}$ , and the feature-extraction unit holds this.

[0021] Weighted average of two covariances from which the covariance weighted average generation means in the feature-extraction unit 4 was acquired, i.e., the model vector covariance  $C_m$  and the model-input fluctuation covariance  $C_p$ ,  $C_s = \alpha C_m + (1 - \alpha) C_p \dots (1)$

( $\alpha$  is calculated according to real number) of  $0 < \alpha < 1$ , and generates Matrix  $C_s$ . Since  $\alpha$  needs to determine a value according to the property of a video camera or an image scanner and needs to determine an optimum value according to the image quality of a model image etc., it actually tries recognition and calculates a value. For example, what is necessary is to set initial value of  $\alpha$  to 0.5, to make it change little by little and just to decide a value so that a recognition rate may improve.

[0022] Next, it opts for selection of the feature space which was suitable for recognition of a pattern using these covariances, i.e., the concrete mechanism of a feature extraction. Here, the feature extraction from a pattern puts projecting the pattern (it considering as  $N$  dimension) of a basis on the space (for example,  $K$ -dimensional  $[K]$ ,  $K < N$ ) of a lower dimension. Choosing a feature space is choosing  $K$  axes of coordinates (vector) which constitute such  $K$ -

dimensional space and which intersect perpendicularly, and, therefore, it is in charge of applying the linear transformation (matrix) constituted by such vector with a feature extraction. For this reason, the space of a model pattern and the space of a fluctuation vector are orthogonalized by conversion which diagonalizes Matrix Cs and the model vector covariance Cm to coincidence. This principle is as follows.

[0023] Matrix Cs is the first diagonalization means.  $C_s = (AQ^{-1/2})(Q^{1/2}AT) \dots (2)$

(A is the normalization characteristic vector matrix of Cs)

(Diagonal matrix which consists of characteristic value to which Q corresponds)

(— Q — spectral decomposition of the square root matrix of  $1/2Q$  and the AT is carried out like transposed-matrix) of A, and matrix  $D^{**}Q^{-1/2}AT$  is outputted.

[0024] On the other hand, Covariance Cm is the 2nd [ after being copied by DCmDT by Conversion D ] diagonalization means.  $DCmDT = BPBT \dots (3)$

(B is the normalization characteristic vector matrix of DCmDT)

Spectral decomposition is carried out like (the diagonal matrix which consists of characteristic value to which P corresponds), and Matrix B is outputted.

[0025] A feature-extraction means is matrix  $Q^{-1/2}AT$  which is these outputs, and based on B.  $H^{**}WB^{*}TQ^{-1/2}AT \dots (4)$

( $W^{**}diag \dots \alpha_1, \alpha_2, \alpha_N$ ) and  $\alpha_i$  generate Matrix H according to suitable non-negative-number), and hold this. This matrix H is a matrix which performs a feature extraction.  $\alpha_i$  is a multiplier which carries out weighting to the description, and it is determined by the approach of calculating an optimum value, trying so that a recognition rate may improve.

[0026] Here, it is Matrix L.  $L^{**}BTQ^{-1/2}AT \dots (11)$

A definition is given.

[0027] Matrix H performs conversion of constant twice to each component after application of Matrix L. Now, the model vector M and input-vector I are received in Matrix L.  $M^{**}LM, I^{**}LI \dots (12)$

When it is alike, and it follows and application, i.e., a feature extraction, is performed, Matrix Cs and the model vector covariance Cm are each by this conversion L.  $L C_s \rightarrow C_s' = \alpha C_m' + (1-\alpha) C_p' = \alpha \text{phasigma}(LM) \text{ and } (LM)^T + (1-\alpha) \text{phasigma}(L(M-I))(L(M-I))^T = \alpha \text{phasigma}(LMTLT)$

$+ 1-\alpha \text{phasigma}(L(M-I)(M-I)^T)$

$= \alpha L C_m L^T + (1-\alpha) L C_p L^T = L(\alpha C_m + (1-\alpha) C_p) L^T = L C_s L^T = B^* T Q^{-1/2} A^* Q A T A Q^{-1/2} B = E$  (E is a unit matrix)  $\dots (13)$

$L C_m \rightarrow C_m' = \text{phasigma}(LM) \text{ and } (LM)^T = \text{phasigma}(BTDM)(MTDTB)$

$= B^* T D C_m D^* T B = B^* T B P B^* T = P \dots (14)$

$**$  — it is changed into a unit matrix E and a diagonal matrix P like.

[0028] To coincidence, it is also a formula 1 to the model-input fluctuation covariance Cp.  $E = L C_s L^T = \alpha L C_m L^T + (1-\alpha) L C_p L^T = \alpha P + (1-\alpha) C_p' C_p' = (E - \alpha P) / (1-\alpha) \dots (15)$

A diagonal matrix is diagonalized for (P and the real number of  $0 < \alpha < 1$  and E are diagonalized for alpha like unit-matrix).

[0029] Conversion by the formula 12 shows that model vector covariance Cm' and model-input fluctuation covariance Cp' have a characteristic vector in common more clearly than the step of a formula 15. further — the characteristic value of a formula 15 to the former — descending order —  $x_1 > x_2 > x_3 > \dots$  the characteristic value of the shaft with which the latter corresponds if  $> x_N$  (all — a non-negative one) —  $y_1 = (1 - \alpha x_1) / (1 - \alpha)$ ,  $y_2 = (1 - \alpha x_2) / (1 - \alpha)$ , and  $\dots y_N = (1 - \alpha x_N) / (1 - \alpha)$

Since it becomes, it is  $y_N > y_{N-1} > \dots$  to descending order... It is set to  $> y_1$  and the ranking of characteristic value is reversed completely.

[0030] Since the characteristic value of a covariance matrix shows distribution (square) in the direction of a corresponding characteristic vector, i.e., the breadth of distribution, by conversion of a formula 12, the space which a model pattern and a model-input fluctuation vector occupy will share all the shafts of distribution, and the ranking of the magnitude of the breadth in shaft orientations will reverse it. That is, it can be said that the space of a model pattern and the space of a model input fluctuation vector intersect perpendicularly. Matrix H is expanding the difference of the breadth of distribution further by each shaft orientations after conversion of Matrix L, and emphasizes this orthogonalization.

[0031] The above is an off-line process, the average fluctuation inclination from the model of an input configuration is caught, and the concrete mechanism of the feature extraction suitable for recognition is determined by this. In the case of pattern recognition (matching with a registered model), it is beforehand inputted off-line through a model pattern input means 2 by which the input of a model pattern also contains a database facility.

[0032] At the time of activation of pattern recognition, it is incorporated from a video camera and a feature-extraction unit calculates feature-vector I' according to  $I'^{**}H$  to the new input face image I to which predetermined processing was performed. Judgment unit  $\|M' - I'\|$  ( $\|*\|$  is Euclidean distance)  $\dots (6)$

A model face with the feature vector made into min is chosen from the feature vectors {M'} of the model image which the feature-extraction unit holds, and is outputted as a recognition result.

[0033] (Gestalt of the 2nd operation) The 2nd operation gestalt of this invention is a face image collating unit which collates the input image photograph inputted as the input face image inputted from the video camera etc. from the image scanner etc., and judges whether it is in agreement. Hereafter, the case where the pattern recognition and the collating unit of this invention are applied to face image collating is explained using Fig. 1.

[0034] The model pattern covariance  $C_m$  is calculated using the model person face image set  $\{M\}$  inputted into the database of the image scanner equipment which is the model pattern input means 2. The count approach of  $C_m$   $C_m = \sum M M^T$  ... (9)

(MT takes the transposed matrix of Matrix  $M$ , and the sum about all sample models  $\{M\}$ .) — it follows.

[0035] The input configuration input means 1 is constituted by a video camera, a digitizer, and the image memory. The model-input fluctuation vector covariance  $C_p$  actually inputs an input face vector  $\{I\}$  (input configuration), and is calculated by the formula 10 from a difference with a corresponding model face pattern. Count of two covariances  $C_m$  and  $C_p$  is carried out by the common covariance count unit 3 above. The information on these covariances is sent to the feature-extraction unit 4. In the feature-extraction unit 4, first, the weighted average  $C_s$  of two covariances is calculated according to a formula 1, and the feature-extraction matrix  $H$  is generated and held through coincidence diagonalization of  $C_s$  and  $C_m$  as explained in full detail previously. The above is off-line processing.

[0036] At the time of collating activation, it is incorporated from a video camera and the feature-extraction unit 4 calculates feature-vector  $I'$  to the new input face image  $I$  to which predetermined processing was performed according to  $I' = H I$ . An input face image fully controls lighting etc. and enables it to photo the best image.

[0037] In a face image collating unit, since the model face vector  $M$  is inputted from an image scanner at the time of activation, the feature-extraction unit 4 extracts feature-vector  $M'$  according to  $M' = H M$  at the time of activation. Since a model image inputs a photograph with a scanner, a changed part by the difference of the photography conditions of a photograph is inputted as it is.

[0038] At the judgment unit 5, it is from  $M'$  and  $I'$ .  $(M' - I') / (|M'| |I'|)$  ... (7)

The inner product of a vector and  $|*|$  calculate the value defined by magnitude-of-a-vector), and  $((* \text{ and } *)$  output how [ with collating right by whether it is more than the constant value that the value defined beforehand ] it is.

[0039] It will be judged whether the best image photoed on that spot and the image of the photograph containing a changed part are inputted, they are mapped to a model and the space which a changed part separated, the amount corresponding to the cosine of the include angle between two vectors is calculated, and a photograph is in agreement with a person. The description which distinction tends to attach can be chosen and collated by adjusting suitably the weight of  $W$  at the time of opting for Conversion  $H$ .

[0040]

[Effect of the Invention] As mentioned above, by this invention, it asks for conversion which makes the space which a model pattern occupies, and the space which a model-input fluctuation vector occupies intersect perpendicularly, and applies to face image recognition and collating. Since a model-input fluctuation vector is the gap from the model pattern with which an input configuration corresponds, if an input and a model are collated in the space where a model pattern exists after conversion, it can take and remove this gap. Moreover, any photographs of his face can be collated with a person in a high precision from many face images and photographs of his face by asking for the conversion which makes a model and a changed part cross at right angles beforehand, carrying out a feature extraction using this conversion, and collating with a photograph the face which does not belong to the set of a model.

[0041] therefore, compared with a conventional method, it is markedly alike, highly precise face image recognition and collating can be realized, and the effectiveness is very large.

---

[Translation done.]

**\* NOTICES \***

JPO and NCIP are not responsible for any damages caused by the use of this translation.

- 1.This document has been translated by computer. So the translation may not reflect the original precisely.
- 2.\*\*\* shows the word which can not be translated.
- 3.In the drawings, any words are not translated.

---

**DESCRIPTION OF DRAWINGS**

---

[Brief Description of the Drawings]

[Drawing 1] It is drawing showing the configuration of the face image recognition and collating unit by this invention.

[Description of Notations]

- 1 Input Configuration Input Means
  - 2 Model Pattern Input Means
  - 3 Covariance Count Unit
  - 4 Feature-Extraction Unit
  - 5 Judgment Unit
- 

[Translation done.]



## \* NOTICES \*

JPO and NCIPJ are not responsible for any damages caused by the use of this translation.

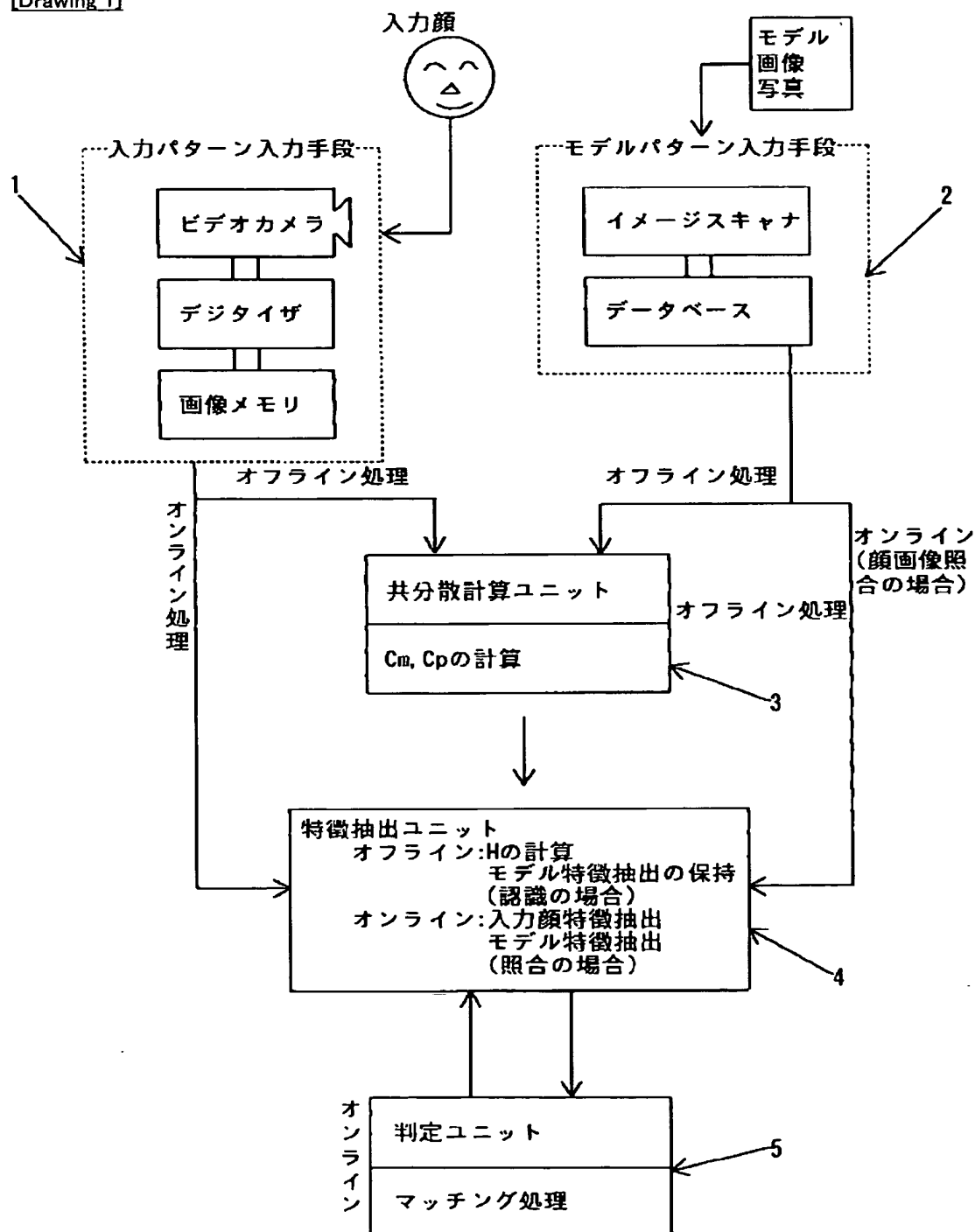
1.This document has been translated by computer. So the translation may not reflect the original precisely.

2.\*\*\* shows the word which can not be translated.

3.In the drawings, any words are not translated.

## DRAWINGS

[Drawing 1]



---

[Translation done.]

## \* NOTICES \*

JPO and NCIP are not responsible for any damages caused by the use of this translation.

- 1.This document has been translated by computer. So the translation may not reflect the original precisely.
- 2.\*\*\*\* shows the word which can not be translated.
- 3.In the drawings, any words are not translated.

## CORRECTION OR AMENDMENT

[Kind of official gazette] Printing of amendment by the convention of 2 of Article 17 of Patent Law

[Section partition] The 3rd partition of the 6th section

[Publication date] October 25, Heisei 14 (2002. 10.25)

[Publication No.] JP,10-171988,A

[Date of Publication] June 26, Heisei 10 (1998. 6.26)

[Annual volume number] Open patent official report 10-1720

[Application number] Japanese Patent Application No. 8-339114

[The 7th edition of International Patent Classification]

G06T 7/00

[F]

G06F 15/62 465 K

[Procedure revision]

[Filing Date] July 17, Heisei 14 (2002. 7.17)

[Procedure amendment 1]

[Document to be Amended] Specification

[Item(s) to be Amended] Claim

[Method of Amendment] Modification

[Proposed Amendment]

[Claim(s)]

[Claim 1] The pattern recognition and the collating unit characterized by providing the following. A model pattern input means to input the model pattern M (for it to also be called a model vector) An input configuration input means to input input configuration I for recognition (for it to also be called an input vector) The model vector covariance matrix Cm for which it asked from said model pattern M From the model-input fluctuation covariance matrix Cp for which it asked from the fluctuation vector which deducted input configuration I which corresponds from said model pattern M A feature-extraction matrix operation means to hold beforehand in quest of the matrix H for feature extractions which carries out linear transformation so that the distribution space of a model pattern and the distribution space of a fluctuation vector may intersect perpendicularly mostly, A feature-extraction means to extract feature-vector M' from the product of said model pattern M and said matrix H, and to extract feature-vector I' from the product of said input configuration I and said matrix H at the time of recognition activation, A judgment means to judge to which model an input configuration corresponds the model pattern which has a feature vector with the smallest distance of said feature-vector I' and said feature-vector M' by the header and this

[Claim 2] Said feature-extraction matrix operation means is the pattern recognition and a collating unit according to claim 1 characterized by diagonalizing the weighted average matrix of said model vector covariance matrix Cm and said model-input fluctuation covariance matrix Cp, and searching for said matrix H.

[Claim 3] Said feature-extraction matrix operation means is the pattern recognition and a collating unit according to claim 2 characterized by searching for the matrix H which projects an input vector on the space which diagonalizes the weighted average matrix of said model vector covariance matrix Cm and said model-input fluctuation covariance matrix Cp, diagonalizes said model vector covariance matrix Cm, and intersects perpendicularly with the distribution space of a fluctuation vector mostly based on those results.

[Claim 4] Said feature-extraction matrix operation means is a weighted average with said model vector covariance matrix Cm and said model-input fluctuation covariance matrix Cp.

$Cs = \alpha Cm + (1 - \alpha) Cp$  (alpha is the real number of  $0 < \alpha < 1$ ) ... (1)

The matrix Cs of the output of a covariance weighted average generation means to be alike, to follow and take and to newly generate Matrix Cs, and said covariance weighted average generation means

$Cs = (AQ \ 1/2) (Q1/2AT) \dots (2)$

(A is the normalization characteristic vector matrix of Cs)

(Diagonal matrix which consists of characteristic value to which Q corresponds)

(Q the square root matrix of  $1/2Q$  and AT transposed matrix of A)

\*\* — spectral decomposition is carried out like and it lines up from this

$D^{**}Q^{-1/2}AT$  ( $Q^{-1/2}$  are the inverse matrix of the square root matrix of Matrix Q)

The diagonalization means of \*\*\*\*\* 1st,

The matrix  $DCmDT$  which changed the model pattern covariance matrix  $Cm$  according to Matrix D

$DCmDT=BPBT$  ... (3)

(B is the normalization characteristic vector matrix of  $DCmDT$ )

(Diagonal matrix which consists of characteristic value to which P corresponds)

\*\* — the 2nd diagonalization means which carries out spectral decomposition like and acquires Matrix B,

output  $Q^{-1/2}$  of said 1st and 2nd diagonalization means — use AT and B

$H^{**}WBQTQ<SUP>-1/2AT$  ... (4)

( $W^{**}diag(\alpha_1, \alpha_2, \dots, \alpha_n)$  and ( $\alpha_i$  are suitable non-negative-number))

The pattern recognition and the collating unit according to claim 2 characterized by having a means for it to be alike, and to follow, and to generate and hold Matrix H.

[Claim 5] Said judgment means is the similarity of the feature vector of a model pattern and an input configuration.

$(M'-I') / (|M'| |I'|)$  ... (7)

( $*$ — $*$ ) (the inner product of a vector and  $|*|$  are the magnitude of a vector)

The pattern recognition and the collating unit according to claim 1 characterized by being alike, following and evaluating and judging whether this value of that input configuration and model is the same by whether it is more than constant value.

[Procedure amendment 2]

[Document to be Amended] Specification

[Item(s) to be Amended] 0010

[Method of Amendment] Modification

[Proposed Amendment]

[0010] Moreover, the pattern recognition and the collating unit of claim 5 are the similarity of the feature vector of a model and an input configuration further.

$(M'-I') / (|M'| |I'|)$  ... (7)

( $*$ — $*$ ) (the inner product of a vector and  $|*|$  are the magnitude of a vector)

It is alike, and follows and evaluates and this value has a judgment means by which an input configuration judges whether it is a thing corresponding to that model by whether it is more than constant value.

[Procedure amendment 3]

[Document to be Amended] Specification

[Item(s) to be Amended] 0012

[Method of Amendment] Modification

[Proposed Amendment]

[0012]

[Embodiment of the Invention] A model pattern input means by which invention indicated to claim 1 of this invention inputs the model pattern M (it is also called a model vector). An input configuration input means to input input configuration I for recognition (for it to also be called an input vector). From the model vector covariance matrix for which it asked from said model pattern M, and the model-input fluctuation covariance matrix for which it asked from the fluctuation vector which deducted input configuration I which corresponds from said model pattern M A feature-extraction matrix operation means to hold the distribution space of a model pattern, and the distribution space of a fluctuation vector beforehand in quest of the matrix H for feature extractions orthogonalized mostly. A feature-extraction means to extract feature-vector  $M'$  from the product of said model pattern M and said matrix H, and to extract feature-vector  $I'$  from the product of said input configuration I and said matrix H at the time of recognition activation. The model pattern which has a feature vector with the smallest distance of said feature-vector  $I'$  and said feature-vector  $M'$  A header. It has an operation of recognizing except for a changed part of an input configuration as compared with a model pattern, by providing a judgment means to judge to which model an input configuration corresponds, and making model space and fluctuation space intersect perpendicularly by this. In pattern recognition and a collating unit according to claim 1, said feature-extraction matrix operation means diagonalizes the weighted average matrix of said model vector covariance matrix  $Cm$  and said model-input fluctuation covariance matrix  $Cp$ , and invention indicated to claim 2 of this invention searches for said matrix H, and has an operation of computing the transformation matrix which makes model space and fluctuation space intersecting perpendicularly using a weighted average matrix. Invention indicated to claim 3 of this invention is set to pattern recognition and a collating unit according to claim 2. Said feature-extraction matrix operation means The weighted average matrix of said model vector covariance matrix  $Cm$  and said model-input fluctuation covariance matrix  $Cp$  is diagonalized. Diagonalize said model vector covariance matrix  $Cm$ , and it is based on those results. The matrix H which projects an input vector on the space which intersects perpendicularly with the distribution space of a fluctuation vector mostly is searched for, and it has an operation of computing the transformation matrix which projects a model pattern on space without the effect of a fluctuation vector. Setting invention indicated to claim 4 of this invention to pattern recognition and a collating unit according to claim 2, said feature-extraction matrix operation means is a weighted average with said model vector covariance matrix  $Cm$  and said model-input fluctuation covariance matrix  $Cp$ .

$Cs^{**}\alpha Cm+(1-\alpha) Cp$  ( $\alpha$  is the real number of  $0 < \alpha < 1$ ) ... (1)

The matrix Cs of the output of a covariance weighted average generation means to be alike, to follow and take and to newly generate Matrix Cs, and said covariance weighted average generation means

$C_s = (A Q^{-1/2}) (Q^{-1/2} A^T) \dots (2)$

(A is the normalization characteristic vector matrix of Cs)

(Diagonal matrix which consists of characteristic value to which Q corresponds)

(Q the square root matrix of  $1/2Q$  and  $A^T$  transposed matrix of A)

\*\* — spectral decomposition is carried out like and it lines up from this

$D^{-1/2} Q^{-1/2} A^T$  ( $Q^{-1/2}$  are the inverse matrix of the square root matrix of Matrix Q)

The diagonalization means of \*\*\*\*\* 1st, and the matrix DCmDT which changed the model pattern covariance

matrix Cm according to Matrix D

$DCmDT = B P B^T \dots (3)$

(B is the normalization characteristic vector matrix of DCmDT)

(Diagonal matrix which consists of characteristic value to which P corresponds)

\*\* — output  $Q^{-1/2}$  of the 2nd diagonalization means which carries out spectral decomposition like and acquires

Matrix B, and said 1st and 2nd diagonalization means — use  $A^T$  and B

$H^{-1/2} W B^T Q^{-1/2} A^T \dots (4)$

( $W^{-1/2} \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_n)$  and ( $\alpha_i$  are suitable non-negative-number))

It has a means for it to be alike, and to follow, and to generate and hold Matrix H, and has an operation of generating the matrix H which separates model vector space more strongly from the distribution space of a fluctuation vector using Matrix W based on the result of coincidence diagonalization of a model pattern covariance matrix and a weighted average matrix.

[Procedure amendment 4]

[Document to be Amended] Specification

[Item(s) to be Amended] 0013

[Method of Amendment] Modification

[Proposed Amendment]

[0013] Invention of this invention according to claim 5 is the similarity of the feature vector of a model pattern and an input configuration.

$(M^T - I^T) / (|M^T| |I^T|) \dots (7)$

(\*-\*) (the inner product of a vector and  $|*|$  are the magnitude of a vector)

It has an operation of collating with a model pattern except for a changed part of an input configuration, by it being alike, following and evaluating, providing a judgment means to judge whether this value of that input configuration and model is the same by whether it is more than constant value, and making model space and fluctuation space intersect perpendicularly.

---

[Translation done.]

(19)日本国特許庁 (JP)

(12) 公開特許公報 (A)

(11)特許出願公開番号

特開平10-171988

(43)公開日 平成10年(1998)6月26日

(51)Int.Cl.<sup>6</sup>

G 0 6 T 7/00

識別記号

F I

G 0 6 F 15/62

4 6 5 K

審査請求 未請求 請求項の数2 F D (全 8 頁)

(21)出願番号

特願平8-339114

(22)出願日

平成8年(1996)12月5日

(71)出願人 000005821

松下電器産業株式会社

大阪府門真市大字門真1006番地

(72)発明者 長尾 健司

大阪府門真市大字門真1006番地 松下電器  
産業株式会社内

(72)発明者 相馬 正宜

大阪府門真市大字門真1006番地 松下電器  
産業株式会社内

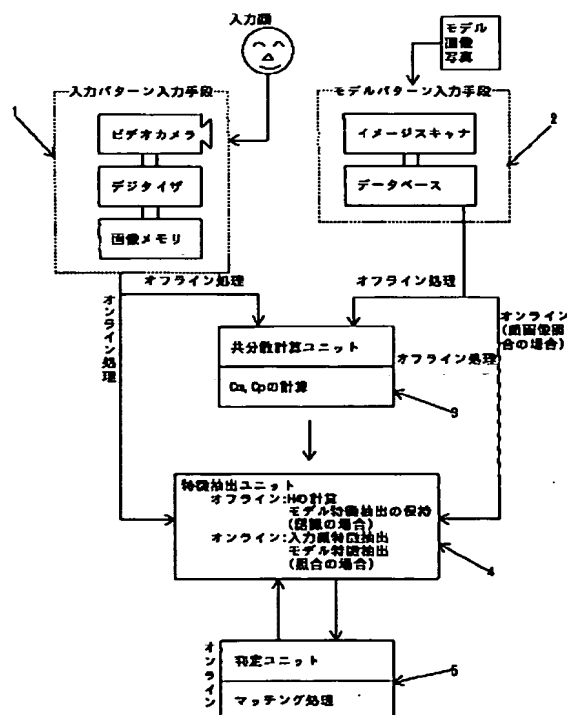
(74)代理人 弁理士 役 昌明 (外2名)

(54)【発明の名称】 パターン認識・照合装置

(57)【要約】

【課題】 顔写真と入力顔画像で、撮影条件が大きく変化している場合でも、入力顔画像がデータベースに登録してあるどの顔写真を認識でき、入力顔画像と特定の顔写真を照合して同一かどうか判定できるようにする。

【解決手段】 多数の顔画像と顔写真を入力して、顔写真からモデルベクトル共分散行列を求め、顔画像と対応する顔写真の差からモデル-入力変動共分散行列を求める。2つの共分散行列を対角化して、モデルベクトルの空間と変動分のベクトルの空間が直交になる変換を求めて、特徴抽出変換とする。特徴抽出変換により、入力顔画像パターンを変換して特徴ベクトルを求め、各モデルベクトルの特徴ベクトルとの距離により、入力顔画像がどの顔写真に対応するかを認識する。また、入力顔画像パターンと顔写真パターンを特徴抽出変換して照合し、人物と顔写真が一致するか否かを判定する。モデル空間と変動分空間を分離して特徴抽出するので、顔写真に撮影条件による変動分があっても、高精度の認識・照合ができる。



(2)

特開平10-171988

1

## 【特許請求の範囲】

【請求項1】 モデルパターンM（モデルベクトルとも呼ぶ）を入力するモデルパターン入力手段と、認識対象の入力パターンI（入力ベクトルとも呼ぶ）を入力する入力パターン入力手段と、モデルベクトルの共分散行列 $C_m$ を入力するモデルベクトル共分散入力手段と、個々

$$C_s \equiv \alpha C_m + (1 - \alpha) C_p \quad (\alpha \text{ は } 0 < \alpha < 1 \text{ の実数}) \quad \dots (1)$$

に従ってとり、新たに行列 $C_s$ を生成する共分散加重平均生成手段と、

$$C_s = (A Q^{1/2}) (Q^{1/2} A^T)$$

(Aは $C_s$ の正規化固有ベクトル行列)

(Qは対応する固有値よりなる対角行列)

( $Q^{1/2}$ はQの平方根行列、 $A^T$ はAの転置行列)のようにスペクトル分解し、これより行列

$$D \equiv Q^{-1/2} A^T \quad (Q^{-1/2} \text{ は行列 } Q \text{ の平方根行列の逆行}$$

$$D C_m D^T = B P B^T$$

(Bは $D C_m D^T$ の正規化固有ベクトル行列)

(Pは対応する固有値よりなる対角行列)のようにスペクトル分解し、行列Bを得る第2の対角化手段と、

$$H \equiv W B^T Q^{-1/2} A^T$$

( $W \equiv \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_n)$ 、( $\alpha_i$ は適当な非負の数))に従って行列Hを生成・保持し、認識のラン

$$M' \equiv H M, I' \equiv H I$$

に従ってそれぞれの特徴ベクトル $M'$ 、 $I'$ を抽出する特徴抽出手段と、

$$\|M' - I'\| \quad (\|*\| \text{ はユークリッド距離}) \quad \dots (6)$$

が最も小さい特徴ベクトルを有するモデルパターンを見つけ出し、これによって入力パターンがどのモデルに対応するかを判定(認識)する判定手段とを具備することを

$$(M' \cdot I') / (\|M'\| \|I'\|)$$

( $(*)$ はベクトルの内積、 $\|*\|$ はベクトルの大きさ)に従って評価し、この値が一定値以上かどうかによって、その入力パターンとモデルが同一のものであるかを判定する判定手段を具備することを特徴とする請求項1記載のパターン認識・照合装置。

## 【発明の詳細な説明】

## 【0001】

【発明の属する技術分野】本発明は、顔写真等を用いたユーザ同定や低ビットレート通信の情報圧縮に用いられるパターン認識・照合装置に関するものであり、特に、人物顔を用いたIDシステム、免許証携帯者の認証、マンマシンインターフェースやセキュリティのためのパターン認識・照合装置において、変動成分をモデル成分と直交するように変換した空間で認識・判定するパターン認識・照合装置に関するものである。

$$M = \sum \gamma_i E_i, \quad I = \sum \gamma_i' E_i$$

( $\gamma_i$ はMのi成分、 $\gamma_i'$ はIのi成分)

(和は、 $i = 1 \dots p$ についてとる)に示す通り、p個の基底ベクトル $E_i$ ( $i = 1 \dots p$ )の線形結合で近似し、近似データ間で照合をとるものである。

2

のモデルパターンから対応する入力パターンへの変動の共分散行列 $C_p$ を予め学習させ入力するモデル入力変動共分散入力手段と、前記モデルベクトル共分散入力手段から入力されたモデルベクトル共分散行列と前記モデル入力変動共分散入力手段から入力されたモデル入力変動共分散行列との加重平均を

前記共分散加重平均生成手段の出力の行列 $C_s$ を

$$\dots (2)$$

列)

を得る第1の対角化手段と、

モデルパターン共分散行列 $C_m$ を行列Dによって変換した行列 $D C_m D^T$ を

$$\dots (3)$$

前記第1及び第2の対角化手段の出力 $Q^{-1/2} A^T$ 、Bを用いて

$$\dots (4)$$

タイムにモデルパターンMと入力パターンIから

$$\dots (5)$$

前記特徴抽出手段が抽出した入力パターンIの特徴ベクトル $I'$ とモデルパターンMの特徴ベクトル $M'$ との距離

$$\dots (6)$$

特徴とするパターン認識・照合装置。

【請求項2】 モデルパターンと入力パターンの特徴ベクトルの類似性を

$$\dots (7)$$

## 【0002】

【従来の技術】パターン認識(例えば顔画像認識や音声認識)の技術分野において最近注目を集めている方式は、データベースに登録されたモデル集合から計算される2次の統計量(共分散)をもとにパターンの分布、即ち、上述したデータ空間内にパターンの集合が占める部分を推定し、これをもとに、パターンからの特徴抽出を行なうものである。例えば、よく知られたKL(Karhunen-Loeve)展開方式は、KL展開によって特徴抽出を行なうもので文献 M.Turk & A.Pentland: "Face Recognition Using Eigenfaces" Proceedings of IEEE, CVPR91.

に詳しく述べられており、他の方法もこれに準じたものが多い。

【0003】KL法では、モデル画像Mおよび入力パターンIを

$$\dots (8)$$

【0004】KL法は、この基底ベクトルとして、w個の教示パターンデータから得られる共分散行列の固有値の大きいものからp個(例えば100個程度)のものに対応する固有ベクトルを用いる。その基底ベクトルによっ

3

て空間を構成すれば、

(1) 射影された教示データが最もよく分離される、即ち、区別しやすくなる。

(2) パターンに含まれるノイズ等、不規則に現れる成分(変動)を取り除くことができる。

という利点を有すると考えられている。このKL法において注意すべき点は、モデルパターン集合から得られる統計量に基づいて推定されるパターンベクトルの分布が一般性を持っていること、即ち、それが入力のパターンにおいてもおおよそあてはまっていることを仮定している点である。

【0005】実際、例えば顔画像認識において、入力パターンのモデルからの変動がそれほど大きくない場合には非常に精度の高い認識率を達成されることが実験的にも確認されている。

【0006】

【発明が解決しようとする課題】しかし、以上のような従来法では入力パターンとモデルの違いが大きくなる場合には十分な認識率を提供することができないという問題があった。これは、例えば画像認識において入力画像

$$C_s \equiv \alpha C_m + (1 - \alpha) C_p \quad (\alpha \text{ は } 0 < \alpha < 1 \text{ の実数}) \quad \dots (1)$$

に従ってとり、新たに行列  $C_s$  を生成する共分散加重平

$$C_s = (A Q^{1/2}) (Q^{1/2} A^T)$$

( $Q^{1/2}$  は  $Q$  の平方根行列、 $A^T$  は  $A$  の転置行列)

( $A$  は  $C_s$  の正規化固有ベクトル行列)

( $Q$  は対応する固有値よりなる対角行列) のようにスベ

$$D C_m D^T = B P B^T$$

( $B$  は  $D C_m D^T$  の正規化固有ベクトル行列)

( $P$  は対応する固有値よりなる対角行列) のようにスベ

$$H \equiv W B^T Q^{-1/2} A^T$$

( $W \equiv \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_n)$ 、( $\alpha_i$  は適当な非負の数)) に従って行列  $H$  を生成・保持し、ランタイム

$$M' \equiv H M, I' \equiv H I$$

に従って特徴ベクトルを抽出する特徴抽出手段を備える。

$$\|M' - I'\| \quad (\|*\| \text{ はユークリッド距離}) \quad \dots (6)$$

の評価値が最も小さい特徴ベクトルを持つモデルを認識結果として選出する判定手段を有する。

【0010】また、請求項2のパターン認識・照合装置

$$(M' \cdot I') / (\|M'\| \|I'\|)$$

( $(* \cdot *)$  はベクトルの内積、 $\|*\|$  はベクトルの大きさ) に従って評価し、この値が一定値以上かどうかによって、入力パターンがそのモデルに対応するものであるかどうかを判定する判定手段を有する。

【0011】以上において、加重平均化された共分散  $C_s$  及び、モデルベクトル共分散  $C_m$  を対角化手段1及び2を用いて対角化し、得られた行列  $H$  によって特徴抽出を行なうことにより、モデルパターンからの入力パターンの変化が、モデル集合が占める空間に直交するように制御することができる。これによって、モデルと入力パ

(3)

特開平10-171988

4

とモデル画像とで撮影時の照明条件など環境が大きく変化する場合等に発生するもので、現実にはしばしば発生する深刻な問題である。

【0007】従来法における上記問題の原因は、それが、パターンの一般的な分布を、データベースに含まれるモデルパターンの統計量のみを用いて推定できると仮定していることに由来する。

【0008】

【課題を解決するための手段】この問題を解決するために、本発明では、モデル集合から得られる統計量に加えて、入力パターンのモデルからの変化を捉えた統計量も予め学習させ利用する。そのため、本発明では、モデルパターンの共分散行列  $C_m$  (パターンの統計的性質の推定) を入力するモデルベクトル共分散入力手段と、個々のモデルパターンから対応する入力パターンへの変動の共分散行列  $C_p$  (変化の性質を示す統計的情報) を予め学習させ入力するモデルー入力変動共分散入力手段と、モデルベクトル共分散行列とモデルー入力変動共分散行列との加重平均を

均生成手段と、 $C_s$  を

$$\dots (2)$$

クトル分解し行列  $Q^{-1/2} A^T$  を得る第一の対角化手段と、モデルベクトル共分散行列  $C_m$  を、行列  $D \equiv Q^{-1/2} A^T$  を用いて変換した行列  $D C_m D^T$  を

$$\dots (3)$$

クトル分解し行列  $B$  を得る第2の対角化手段と、これらの行列  $Q^{-1/2} A^T$ 、 $B$  を用いて

$$\dots (4)$$

にモデルパターン  $M$  と入力パターン  $I$  から

$$\dots (5)$$

【0009】請求項1のパターン認識・照合装置においては、さらに、入力顔の特徴ベクトルに対して

は、さらに、モデルと入力パターンの特徴ベクトルの類似性を

$$\dots (7)$$

一の違いが大きい場合でも、認識・照合の最終過程においてモデルの占める空間に直交するような方向の特徴を無視することで入力に対応するモデルが正しくマッチされる。以下、この詳細なメカニズムを説明する。

【0012】

【発明の実施の形態】本発明の請求項1に記載した発明は、モデルパターン  $M$  (モデルベクトルとも呼ぶ) を入力するモデルパターン入力手段と、認識対象の入力パターン  $I$  (入力ベクトルとも呼ぶ) を入力する入力パターン入力手段と、モデルベクトルの共分散行列  $C_m$  を入力

50



(4)

特開平10-171988

5

するモデルベクトル共分散入力手段と、個々のモデルパターンから対応する入力パターンへの変動の共分散行列  $C_p$  を予め学習させ入力するモデル入力変動共分散入力手段と、前記モデルベクトル共分散入力手段から入力

$$C_s \equiv \alpha C_m + (1 - \alpha) C_p \quad (\alpha \text{ は } 0 < \alpha < 1 \text{ の実数}) \quad \dots (1)$$

に従ってとり、新たに行列  $C_s$  を生成する共分散加重平均生成手段と、前記共分散加重平均生成手段の出力の行

$$C_s = (A Q^{1/2}) (Q^{1/2} A^T)$$

( $A$  は  $C_s$  の正規化固有ベクトル行列)

( $Q$  は対応する固有値よりなる対角行列)

( $Q^{1/2}$  は  $Q$  の平方根行列、 $A^T$  は  $A$  の転置行列) のようにスペクトル分解し、これより行列

$$D C_m D^T = B P B^T$$

( $B$  は  $D C_m D^T$  の正規化固有ベクトル行列)

( $P$  は対応する固有値よりなる対角行列) のようにスペクトル分解し、行列  $B$  を得る第2の対角化手段と、前記

$$H \equiv W B^T Q^{-1/2} A^T$$

( $W \equiv \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_n)$ 、( $\alpha_i$  は適当な非負の数)) に従って行列  $H$  を生成・保持し、認識のラン

$$M' \equiv H M, I' \equiv H I$$

に従ってそれぞれの特徴ベクトル  $M'$ 、 $I'$  を抽出する特徴抽出手段と、前記特徴抽出手段が抽出した入力パター

$$\|M' - I'\| \quad (\|*\| \text{ はユークリッド距離}) \quad \dots (6)$$

が最も小さい特徴ベクトルを有するモデルパターンを見出し、これによって入力パターンがどのモデルに対応するかを判定(認識)する判定手段とを具備するものであり、モデル空間と変動空間を直交させることにより、入力パターンの変動分を除いてモデルパターンと比較し

$$(M' \cdot I') / (\|M'\| \|I'\|)$$

( $(*)$  はベクトルの内積、 $\|*\|$  はベクトルの大きさ) に従って評価し、この値が一定値以上かどうかによって、その入力パターンとモデルが同一のものであるかを判定する判定手段を具備するものであり、モデル空間と変動空間を直交させることにより、入力パターンの変動分を除いてモデルパターンと照合することができるという作用を有するものである。

【0014】(第1の実施の形態) 本発明の第1の実施の形態は、ビデオカメラなどから入力した入力顔画像に一致する顔画像をモデル画像写真のデータベースから選出する顔画像認識装置である。以下、本発明のパターン認識・照合装置を顔画像認識に適用した場合について第1図を用いて説明する。

【0015】入力パターン入力手段1は、入力顔を撮影するビデオカメラと、ビデオカメラのアナログ映像信号をデジタル信号に変換するデジタイザと、デジタル映像信号を記憶する画像メモリにより構成される。モデルパターン入力手段2は、モデル画像写真をスキャンして入力するイメージスキャナと、イメージスキャナから入力されたモデル画像写真をデジタル画像ファイルとして格納するデータベースにより構成される。共分散計算ユニ

6

されたモデルベクトル共分散行列と前記モデル入力変動共分散入力手段から入力されたモデル入力変動共分散行列との加重平均を

列  $C_s$  を

$$\dots (2)$$

$D \equiv Q^{-1/2} A^T$  ( $Q^{-1/2}$  は行列  $Q$  の平方根行列の逆行列)

10

を得る第1の対角化手段と、モデルパターン共分散行列  $C_m$  を行列  $D$  によって変換した行列  $D C_m D^T$  を

$$\dots (3)$$

第1及び第2の対角化手段の出力  $Q^{-1/2} A^T$ 、 $B$  を用いて

$$\dots (4)$$

タイムにモデルパターン  $M$  と入力パターン  $I$  から

$$\dots (5)$$

ン  $I$  の特徴ベクトル  $I'$  とモデルパターン  $M$  の特徴ベクトル  $M'$  との距離

$$\dots (6)$$

て認識することができるという作用を有するものである。

【0013】本発明の請求項2に記載の発明は、モデルパターンと入力パターンの特徴ベクトルの類似性を

$$\dots (7)$$

30

ット3は、入力パターン入力手段1とモデルパターン入力手段2から画像データを入力し、1つの画像データをベクトルとみなして共分散行列を計算する計算装置である。特徴抽出ユニット4は、共分散行列から変換行列を計算するとともに、1つの画像データをベクトルとみなして変換行列によりベクトル変換して特徴ベクトルを計算する計算装置である。判定ユニット5は、特徴ベクトル間の距離や角度を計算する計算装置である。これらの計算装置は、汎用のプロセッサを用いて構成してもよいし、DSPなどの専用のプロセッサを用いて構成してもよい。

40

【0016】入力パターン入力手段1とモデルパターン入力手段2と共分散計算ユニット3と特徴抽出ユニット4により、オフラインのプロセスとして、モデルパターンの空間とモデル入力変動ベクトルの空間を直交化させるような特徴空間の選定を行ない、入力パターン入力手段1とモデルパターン入力手段2と共分散計算ユニット3と判定ユニット5により、オンラインで認識処理を行なう。

50

【0017】最初に、オフラインの処理について説明する。一般にパターンがデータ空間の中で占める空間の次

(5)

特開平10-171988

7

元（例えば顔画像が画像空間全体の中に占める部分の次元）は、もとの空間の次元（例えばピクセル数が10万であれば10万次元）に比べかなり小さく（例えば100次元）になっている場合が多い。同様に、モデル入力の変動ベクトルもデータ空間においては低次元の空間を占め

$$C_m \equiv \Sigma M M^T$$

（ $M^T$ は行列 $M$ の転置行列、和は全ての標本モデル $\{M\}$ についてとる。）に従って直接計算できるが、他の方法で得られたものであっても問題はない。モデルパターンの分布（共分散）を示すものであればよい。この実施形態では、モデルパターン共分散 $C_m$ はモデルパターン入力手段2であるイメージスキャナ装備のデータベースに入力されたモデル人物顔画像集合 $\{M\}$ を用いて計算する。ここで、簡単のためにモデルベクトルの平均

$$C_p \equiv \Sigma (M - I) (M - I)^T$$

（ $(M - I)^T$ は行列 $(M - I)$ の転置行列）

（和は得られた全ての $(M, I)$ のペアについてとる。）に従って直接計算できるが、他の方法で得られたものであってもよい。差ベクトルの分布（共分散）を示すものであればよい。この実施形態では、モデル入力変動ベクトル共分散 $C_p$ は、入力顔ベクトル $\{I\}$ （入力パターン）を実際に入力し、対応するモデル顔パターンとの差から式10に従って計算される。

【0019】以上の2つの共分散 $C_m$ と $C_p$ の計算は、共通の共分散計算ユニット3によって実施される。これらの共分散の情報は、特徴抽出ユニット4に送られる。

$$C_s \equiv \alpha C_m + (1 - \alpha) C_p$$

（ $\alpha$ は $0 < \alpha < 1$ の実数）に従って計算し、行列 $C_s$ を生成する。 $\alpha$ は、ビデオカメラやイメージスキャナの特성에応じて値を決める必要があるし、モデル画像の画質などにも従って最適値を決める必要があるので、実際に認識の試行を行なって値を求める。例えば、 $\alpha$ の初期値を0.5として、認識率が向上するように少しずつ変化させて値を決めればよい。

【0022】次に、これらの共分散を用いてパターンの認識に適した特徴空間の選定、即ち、特徴抽出の具体的なメカニズムを決定する。ここで、パターンからの特徴抽出とは、もとのパターン（ $N$ 次元とする）をより低い次

$$C_s = (A Q^{1/2}) (Q^{1/2} A^T)$$

（ $A$ は $C_s$ の正規化固有ベクトル行列）

（ $Q$ は対応する固有値よりなる対角行列）

（ $Q^{1/2}$ は $Q$ の平方根行列、 $A^T$ は $A$ の転置行列）のようにスペクトル分解され、行列 $D \equiv Q^{-1/2} A^T$ が出力され

$$D C_m D^T = B P B^T$$

（ $B$ は $D C_m D^T$ の正規化固有ベクトル行列）

（ $P$ は対応する固有値よりなる対角行列）のようにスペクトル分解され、行列 $B$ が出力される。

$$H \equiv W B^T Q^{-1/2} A^T$$

（ $W \equiv \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_N)$ 、 $\alpha_i$ は適当な非負の数）に従って行列 $H$ を生成しこれを保持する。この行

8

る。まず、モデルパターンの統計的傾向を示す共分散行列 $C_m$ を、モデルベクトル共分散入力手段から入力する。この共分散行列 $C_m$ は、モデルパターン入力手段から入力されたモデルパターンを用いて

$$\dots (9)$$

ベクトルは0としている。そうでない場合は $M$ を $(M - M_a)$ （ $M_a$ は集合 $\{M\}$ の平均）を用いる。

【0018】また、入力パターンと対応するモデルの差 $(M - I)$ の統計的性質を示す共分散行列 $C_p$ を、モデル入力変動共分散入力手段から入力し、入力の変動傾向を学習させる。この共分散 $C_p$ は入力パターン入力手段から入力される入力パターンのサンプル群と対応するモデルの差を用いて

$$\dots (10)$$

【0020】特徴抽出ユニット4では、まず、2つの共分散の加重平均 $C_s$ を式1に従って計算し、 $C_s$ 、 $C_m$ の同時対角化を経て、特徴抽出行列 $H$ を生成し保持する。画像認識装置の場合は、モデル画像ベクトル $\{M\}$ から特徴ベクトル $\{M'\}$ を抽出し特徴抽出ユニットがこれを保持しておく。

【0021】特徴抽出ユニット4の中の共分散加重平均生成手段が、得られた2つの共分散、即ち、モデルベクトル共分散 $C_m$ とモデル入力変動共分散 $C_p$ の加重平均を

$$\dots (1)$$

元の空間（例えば $K$ 次元、 $K < N$ ）に射影することをさす。したがって、特徴空間を選ぶことは、そのような $K$ 次元の空間を構成する $K$ 個の直交する座標軸（ベクトル）を選ぶことであり、よって特徴抽出とはそのようなベクトルによって構成される線形変換（行列）を適用することにあたる。このために、行列 $C_s$ とモデルベクトル共分散 $C_m$ を同時に対角化する変換によって、モデルパターンの空間と変動ベクトルの空間を直交化する。この原理は以下の通りである。

【0023】行列 $C_s$ は第一の対角化手段によって

$$\dots (2)$$

る。

【0024】一方、共分散 $C_m$ は変換 $D$ によって $D C_m D^T$ に写された後、第2の対角化手段によって

$$\dots (3)$$

【0025】特徴抽出手段は、これらの出力の行列 $Q^{-1/2} A^T$ 、 $B$ をもとに

$$\dots (4)$$

列 $H$ が特徴抽出を行なう行列である。 $\alpha_i$ は、特徴に重みづけする係数であり、認識率が向上するように試行し

50

(6)

特開平10-171988

9

10

ながら最適値を求める方法で決定する。

$$L \equiv B^T Q^{-1/2} A^T$$

と定義する。

【0027】行列Hは、行列Lの適用後各成分に対して

$$M' \equiv LM, I' \equiv LI$$

に従って適用、即ち、特徴抽出を行なうと、この変換Lによって、行列C<sub>s</sub>、モデルベクトル共分散C<sub>m</sub>はそれぞれ

$$\begin{aligned} L \\ C_s \rightarrow C_s' &= \alpha C_m' + (1 - \alpha) C_p' \\ &= \alpha \Sigma (LM) (LM)^T \\ &\quad + (1 - \alpha) \Sigma (L(M - I)) (L(M - I))^T \\ &= \alpha \Sigma (LMM^T L^T) \\ &\quad + (1 - \alpha) \Sigma (L(M - I) (M - I)^T L^T) \\ &= \alpha L C_m L^T + (1 - \alpha) L C_p L^T \\ &= L (\alpha C_m + (1 - \alpha) C_p) L^T \\ &= L C_s L^T \\ &= B^T Q^{-1/2} A^T A Q A^T A Q^{-1/2} B \\ &= E \quad (E \text{ は単位行列}) \end{aligned} \quad \dots (13)$$

$$\begin{aligned} L \\ C_m \rightarrow C_m' &= \Sigma (LM) (LM)^T \\ &= \Sigma (B^T D M) (M^T D^T B) \\ &= B^T D C_m D^T B \\ &= B^T B P B^T B \\ &= P \end{aligned} \quad \dots (14)$$

のように単位行列E、対角行列Pに変換される。

C<sub>p</sub>も

【0028】同時に、式1からモデルー入力変動共分散

$$\begin{aligned} E &= L C_s L^T \\ &= \alpha L C_m L^T + (1 - \alpha) L C_p L^T \\ &= \alpha P + (1 - \alpha) C_p' \\ C_p' &= (E - \alpha P) / (1 - \alpha) \end{aligned} \quad \dots (15)$$

(Pは対角行列、αは0<α<1の実数、Eは単位行列)のように対角化される。

【0029】式15のステップより明らかに、式12による変換によって、モデルベクトル共分散C<sub>m</sub>'とモデルー入力変動共分散C<sub>p</sub>'は、固有ベクトルを共通に持つことがわかる。さらに式15から、前者の固有値を降順にx<sub>1</sub>>x<sub>2</sub>>x<sub>3</sub>>...>x<sub>N</sub>(全て非負)とすると、後者の対応する軸の固有値は

$$\begin{aligned} y_1 &= (1 - \alpha x_1) / (1 - \alpha), \\ y_2 &= (1 - \alpha x_2) / (1 - \alpha), \\ &\dots \end{aligned}$$

$$y_N = (1 - \alpha x_N) / (1 - \alpha)$$

となるので、降順にy<sub>N</sub>>y<sub>N-1</sub>>...>y<sub>1</sub>となり、固有値の順位が完全に逆転する。

【0030】共分散行列の固有値は、対応する固有ベクトルの方向での分散、即ち、分布の広がり(の2乗)を示すものであるから、モデルパターンとモデルー入力変動ベクトルの占める空間は式12の変換によって、分布の

$$\|M' - I'\| \quad (\|*\| \text{ はユークリッド距離}) \quad \dots (6)$$

を最小にする特徴ベクトルを持つモデル顔を、特徴抽出

【0026】ここで、行列Lを

$$\dots (11)$$

定数倍の変換をほどこすものである。今、行列LをモデルベクトルM、及び、入力ベクトルIに対して

$$\dots (12)$$

れ

軸を全て共有し、かつ、軸方向での広がり(の大きさ)の順位が逆転することになる。即ち、モデルパターンの空間とモデル入力変動ベクトルの空間は直交すると言える。行列Hは行列Lの変換後、各軸方向で分布の広がり(の差)をさらに拡大することで、この直交化を強調したものである。

【0031】以上がオフラインのプロセスであり、これによって、入力パターンのモデルからの平均的な変動傾向を捉え、認識に適した特徴抽出の具体的メカニズムが決定される。パターン認識(登録済みのモデルとのマッチング)の場合はモデルパターンの入力もデータベース機能を含むモデルパターン入力手段2を通してオフラインで予め入力されている。

【0032】パターン認識の実行時には、ビデオカメラから取り込まれ、所定の処理を施された新しい入力顔画像Iに対して特徴抽出ユニットが、

$$I' \equiv H I$$

に従って特徴ベクトルI'を計算する。判定ユニットは

50 ユニットが保持しているモデル画像の特徴ベクトル

11

{M'}の中から選び、認識結果として出力する。

【0033】(第2の実施の形態)本発明の第2の実施形態は、ビデオカメラなどから入力した入力顔画像と、イメージスキャナなどから入力した入力画像写真を照合して、一致するか否かを判定する顔画像照合装置である。以下、本発明のパターン認識・照合装置を顔画像照

$$C_m \equiv \Sigma M M^T$$

( $M^T$ は行列Mの転置行列、和は全ての標本モデル{M}についてとる。)に従う。

【0035】入力パターン入力手段1は、ビデオカメラとデジタイザと画像メモリにより構成される。モデル入力変動ベクトル共分散 $C_p$ は入力顔ベクトル{I}

(入力パターン)を実際に入力し、対応するモデル顔パターンとの差から式10により計算される。以上2つの共分散 $C_m$ と $C_p$ の計算は共通の共分散計算ユニット3によって実施される。これらの共分散の情報は、特徴抽出ユニット4に送られる。特徴抽出ユニット4では、まず、2つの共分散の加重平均 $C_s$ を式1に従って計算し、先に詳述した通り $C_s$ 、 $C_m$ の同時対角化を経て特徴抽出行

列Hを生成し保持する。以上がオフライン処理である。

【0036】照合実行時には、ビデオカメラから取り込

$$(M' \cdot I') / (|M'| |I'|)$$

( $(*)$ はベクトルの内積、 $|*|$ はベクトルの大きさ)で定義された値を計算し、その値が予め定めた一定値以上か否かによって、照合が正しいかどうかを出力する。

【0039】その場で撮影した最良の画像と、変動分を含む写真の画像を入力し、それらをモデルと変動分が分離した空間に写像し、2つのベクトルの間の角度の余弦に対応する量を求めて、人物と写真が一致するか否かを判定することになる。変換Hを決める際のWの重みを適当に調節することにより、判別のつきやすい特徴を選んで照合することができる。

【0040】

【発明の効果】以上のように本発明では、モデルパターンが占める空間と、モデル入力変動ベクトルが占める空間を直交させるような変換を求めて、顔画像認識・照合に適用する。モデル入力変動ベクトルは、入力パターンの対応するモデルパターンからのずれであるから、変換後にモデルパターンの存在する空間で入力とモデル

(7)

特開平10-171988

12

合に適用した場合について、第1図を用いて説明する。

【0034】モデルパターン共分散 $C_m$ はモデルパターン入力手段2であるイメージスキャナ装備のデータベースに入力されたモデル人物顔画像集合{M}を用いて計算する。 $C_m$ の計算方法は

$$\dots (9)$$

まれ、所定の処理を施された新しい入力顔画像I'に対して、特徴抽出ユニット4が

$$I' \equiv H I$$

に従って特徴ベクトルI'を計算する。入力顔画像は、照明などを十分に制御して、最良の画像を撮影できるようにする。

【0037】顔画像照合装置では、モデル顔ベクトルMも実行時にイメージスキャナから入力されるので、実行時に特徴抽出ユニット4が

$$M' \equiv H M$$

に従って特徴ベクトルM'の抽出を行なう。モデル画像は、写真をスキャナで入力するので、写真の撮影条件の差による変動分はそのまま入力される。

【0038】判定ユニット5では、M'とI'から

$$\dots (7)$$

を照合すれば、このずれをとり除くことができる。また、多数の顔画像と顔写真から、モデルと変動分を直交させる変換をあらかじめ求めて、この変換を使って特徴抽出して、モデルの集合に属さない顔を写真と照合することにより、どのような顔写真でも高い精度で人物と照合することができる。

【0041】したがって、従来法に比べ格段に高精度な顔画像認識・照合が実現でき、その効果は非常に大きい。

【図面の簡単な説明】

【図1】本発明による顔画像認識・照合装置の構成を示す図である。

【符号の説明】

- 1 入力パターン入力手段
- 2 モデルパターン入力手段
- 3 共分散計算ユニット
- 4 特徴抽出ユニット
- 5 判定ユニット

【図1】

